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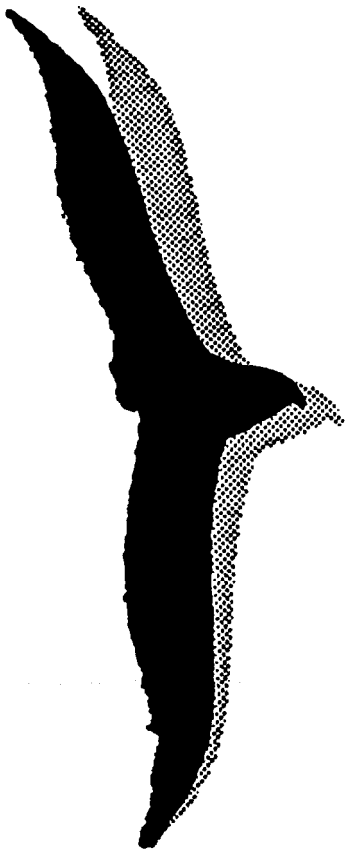
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A Structural Analysis of Job Search Methods and Subsequent Wages

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July 22, 1997



Abstract

In most studies on individual labor market transitions, the search process leading to job offers is a black box. In this paper we specify and estimate a search model that distinguishes between formal (applications) and informal (referrals) search methods. Job offers can be obtained by either method, and the corresponding wage offer distributions **are** allowed to differ. The model allows for search during unemployment as well as search on the job. We conclude that although the method by which jobs are found varies considerably with education and occupation, the use of a particular search method does not result in a higher wage. Moreover, individuals who have an advantage in informal search do not find a job more rapidly, which casts doubt on the hypothesis that the search method is freely chosen by the searcher by comparing costs and returns.

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Keywords: job search, search methods, wages, individual labor market transitions.

1 Introduction

The job search of individuals in the labor market involves a number of choices. Blau and Robins (1990) distinguish four components: the choice of the search method, the effort devoted to each search method, which firms to contact first, and the choice of acceptance criterion. Together these four components determine the job finding rate. However, most studies of the search behavior of workers simply assume that wage offers arrive according to an exogenous stochastic process and that wage offers are random drawings from a given wage offer distribution. Standard job search theory reduces the decision problem of a job searcher to the choice of a reservation wage. This study looks inside the black box of the search process using a structural model in which the job searcher employs two search methods: workers can receive job offers either by direct application to an employer or by referral by an (other) employed person. Associated with these two types of offers are two distinct wage offer distributions. A test of the equality of these distributions is an important contribution of this paper. In the sequel we refer to these search methods as the formal (application) and the informal (referral) search method.

The use of different sources of information is one of the key elements in the search process of individuals. However, little effort has been made to incorporate multiple information sources in a structural model. Holzer (1988) argues that costs (time and effort spent on searching) as well as benefits (effectiveness of search; the number of acceptable job offers) play a role in the choice of search method. In general, the costs are at the expense of current income, while the benefits are in terms of higher expected future income. It is argued that the money and time costs associated with referral by other workers are low in comparison to the costs associated with formal applications. From the point of view of the employer, informal search may be more effective than formal search, because they consider referrals from their workers as more reliable than direct applications. Employees have an incentive to refer well-qualified workers, since they feel responsible for the applicants. Hence referral helps in solving the selection problem of the employer. Montgomery (1991) develops a selection model in which the network density of a worker plays a crucial role in determining his/her labor market outcomes. Montgomery argues that informal search generates higher profits for firms, and that wages of workers with an extensive social network are higher, because they are more likely to be referred by other workers.

Even if applicants have the same productivity, in equilibrium wage offers obtained by informal search may be higher than those obtained by formal search.

Mortensen and Vishwanath (1993, 1994) develop an equilibrium search model with a formal and an informal search channel. In this model, employed workers search on the job for jobs with higher wages, so that in equilibrium firms paying high wages also have a relatively large workforce. If a worker searches by way of referral by currently employed workers, then the probability that of getting an offer of a particular firm is proportional to the size of that firm. If a worker searches by way of applications then sampling of firms is uniform. Hence, searching by contacting workers instead of firms generates higher wage offers. As a result, individuals who have access to informal search channels will earn a higher wage, even if they are equally productive as individuals without access to the informal channel.

There is a substantial descriptive literature on job offer arrival rates and labor market transitions of employed and unemployed workers. In this literature, data on search methods, like the number of methods used, are sometimes used as an indicator for the search intensity of job seekers (e.g. Holzer (1988)). Using Dutch data, Lindeboom, Van Ours and Renes (1994) find that: (1) The majority of job seekers uses both formal and informal methods. (2) Employed workers have a higher job offer arrival rate than unemployed workers (Blau and Robins (1990) obtain the same conclusion with US data), and (3) Informal wage offers have a relatively large conditional acceptance probability. The latter result is also found by Holzer (1988). Finally, Thomas (1996) estimates a competing risks model in which the job finding rate of unemployed job seekers differs between random and selective search. His results indicate that those individuals who search selectively have shorter unemployment spells than those who search randomly.

None of these empirical studies addresses the extent to which different channels result in jobs with different wages. As such, they provide incomplete descriptions of the effects of using different search methods. Wage differentials by search method are important because they provide a reason for why job seekers would prefer a particular search method. If wage differentials are absent then the relative cost and the number of job offers are the only relevant characteristics of the search methods. Such information is useful for policy purposes, for example for an evaluation of the efficiency of subsidies that are allocated to stimulate the use of a particular method.

In this paper, we specify and estimate a structural job search model in which job seekers employ formal and informal search methods. The model allows for search during unemployment as well as search on the job, and we estimate the model with longitudinal data on individual wages, transitions between individual labor states, and durations spent in those states. In the model, the distribution of

wage offers is allowed to depend on the search method that was used to find the corresponding job offer. This provides a direct test of models that predict that the distributions for different search methods do not coincide (Montgomery (1991), Mortensen and Vishwanath (1993)). Such a test is hampered by the fact that we only observe accepted wages. It is well-known that equality of the distributions of accepted wages does not imply equality of the wage offer distributions. We should stress that the theoretical models in the studies above are such that in equilibrium the unemployed workers always accept all wage offers, so that these distributions coincide. A necessary assumption for this is that workers are homogeneous in terms of their opportunity costs of employment. However, in this paper we do not impose such equilibrium models from the outset, and we do not want to rule out in advance that (some) workers reject low wage offers.

This means that we have to make inferences on the difference between two wage offer distributions even though we do not have data on rejected wage offers. We deal with this problem in a number of ways. For example, we show that the sign of the relation between differences in mean accepted wages and differences in acceptance probabilities is unambiguous for a wide class of probability distributions. In the empirical analysis, we specify our structural model in terms of identified distributions and transition intensities.¹ As a consequence, our empirical structural model makes minimal assumptions on the search strategy of unemployed workers. In particular, we do not require that the reservation wage of the unemployed satisfies the Bellman equation for the optimal strategy. The Bellman equation is used in the second stage of our estimation procedure to estimate the discount rate. In the second stage it is also possible to test whether the lowest observed wages are significantly larger than the theoretically predicted optimal reservation wage, in order to test whether all wage offers are acceptable, i.e. whether the distribution of accepted wages coincides with the wage offer distribution. Another test on the same hypothesis exploits variation of unemployment benefits levels across individuals. Finally, we test whether the use of a search method is sensitive to one of the components of its cost.

Our conclusion is that the two search methods considered in this study do not generate wage offers that are significantly different. Moreover, individuals with a relatively low cost of using referrals do not find jobs more rapidly by

¹This is an innovation with respect to the traditional approach in structural estimation of job search models (see Wolpin (1987) and Van den Berg (1990b) for examples). In the literature, job offer arrival rates and wage offer distributions are estimated as structural determinants. However, the estimates are sensitive to ad-hoc functional form assumptions on the shape of the wage offer distribution.

the informal search method. Hence, when analyzing the search behavior of the employed and unemployed, the distinction between formal and informal search is largely irrelevant.

The outline of the paper is as follows. In Section 2 we specify the theoretical model. Section 3 discusses the data. Identification issues and the empirical implementation of the model are considered in Section 4. Section 5 contains the estimation results, and Section 6 concludes.

2 The model

2.1 The basic model

The model is based on the standard job search model with on-the-job search (see e.g. Mortensen (1986)). We generalize the model by distinguishing between formal and informal search channels that have distinct wage offer distributions and offer arrival rates.

Individuals maximize their expected discounted income over an infinite time horizon. Income is equal to the benefit level b for unemployed individuals and to the current wage w for employed individuals. Wage offers are obtained by the formal and informal search method at a rate of, respectively, λ_{uf} and λ_{ug} while unemployed, and λ_{ef} and λ_{eg} while employed. The corresponding wage offers are random drawings from (absolutely continuous) distributions with c.d.f. F and G , respectively, that are assumed to be identical for the unemployed and the employed. The employed are laid off at rate δ . In the sequel, the subscripts u, e are used to distinguish between the unemployed and the employed, and the subscripts f, g to make a distinction between the formal and informal search methods.

All parameters and distributions are assumed to be constant over time. The optimal strategy of an unemployed individual is characterized by a reservation wage r that satisfies

$$\rho R = b + \int_r^\infty [W(x) - R] (\lambda_{uf} dF(x) + \lambda_{ug} dG(x)) \quad (1)$$

where $W(w)$ denotes the expected present value of holding a job with wage w , R denotes the expected present value of being unemployed, and ρ denotes the discount rate.

In the absence of fixed costs associated with job-to-job mobility, the optimal strategy of an employed individual is to accept a wage offer if and only if it

exceeds his current wage. Thus the income flow of being employed at wage w is

$$\rho W(w) = w + \int_w^\infty [W(x) - W(w)] (\lambda_{uf} + \lambda_{ef} dF(x) + \lambda_{ug} + \lambda_{eg} dG(x)) + \delta [R - W(w)] \quad (2)$$

Differentiating this expression with respect to w (technicalities are similar to those in the basic model; see e.g. Albrecht, Holmlund and Lang (1991)), we get

$$W'(w) = \frac{1}{\rho + \delta + \lambda_{ef} \bar{F}(w) + \lambda_{eg} \bar{G}(w)} \quad (3)$$

where

$$\bar{F}(w) = 1 - F(w), \quad \bar{G}(w) = 1 - G(w) \quad (4)$$

The denominator of equation (3) can be interpreted as the rate at which the value of a job is discounted. It is the sum of the discount rate and the job leaving rate.

The expected discounted value of holding a job with wage r , $W(r)$, is equal to the expected discounted value of being unemployed, R . Evaluating (2) in r and using the resulting expression and (1) to eliminate r , we obtain

$$r = b + \int_r^\infty [W(x) - R] ((\lambda_{uf} - \lambda_{ef}) dF(x) + (\lambda_{ug} - \lambda_{eg}) dG(x)) \quad (5)$$

Partial integration and substitution of (3) gives

$$r = b + \int_r^\infty \frac{(\lambda_{uf} - \lambda_{ef}) \bar{F}(w) + (\lambda_{ug} - \lambda_{eg}) \bar{G}(w)}{\rho + \delta + \lambda_{ef} \bar{F}(w) + \lambda_{eg} \bar{G}(w)} dw \quad (6)$$

If both $\lambda_{uf} = \lambda_{ef}$ and $\lambda_{ug} = \lambda_{eg}$, then individuals are indifferent between searching while unemployed or employed, and the reservation wage is equal to the benefits level. If the arrival rates while employed exceed those while unemployed, the unemployed accept wages below the level of unemployment benefits.

The unemployed may find a job by either the formal or the informal search method. The transition rates equal the product of the corresponding arrival rates and the acceptance probabilities

$$\begin{aligned} \theta_{uf} &= \lambda_{uf} \bar{F}(r) \\ \theta_{ug} &= \lambda_{ug} \bar{G}(r) \end{aligned} \quad (7)$$

The rate at which the unemployed find a job, denoted by θ_u , is equal to the sum of these transition rates. In the same way, the transition rates for an employee who holds a job with wage w are

$$\begin{aligned}\theta_{ef}(w) &= \lambda_{ef}\bar{F}(w) \\ \theta_{eg}(w) &= \lambda_{eg}\bar{G}(w)\end{aligned}\tag{8}$$

and the job leaving rate, $\theta_e(w)$, is the sum of these transition rates and 6.

The comparative statics for this extension of the job search model with on-the-job search are similar to those for the original model. We consider the semi-elasticity of r and the job finding and leaving rates with respect to the fraction of job offers that are obtained through the informal channel

$$\alpha_k = \frac{\lambda_{kg}}{\lambda_{kf} + \lambda_{kg}}\tag{9}$$

with $k = u, e$. These semi-elasticities can be written as

$$\frac{d \ln r}{d \alpha_u} = \frac{d \ln r}{d b} \lambda_u \int_0^\infty \frac{\bar{G}(x) - \bar{F}(x)}{\rho + \delta + \theta_e(x)} dx\tag{10}$$

$$\frac{\partial \ln \theta_e(w)}{\partial \alpha_e} = \frac{\bar{G}(w) - \mathbf{F}(\mathbf{w})}{(\mathbf{1} - \alpha_e)\bar{F}(\mathbf{w}) + \alpha_e\bar{G}(w)}\tag{11}$$

$$\frac{a \ln \theta_u}{\partial \alpha_u} = \frac{\bar{G}(r) - \mathbf{F}(r)}{(1 - \alpha_u)\bar{F}(r) + \alpha_u\bar{G}(r)} + \frac{\partial \ln \theta_u}{\partial \ln r} \frac{d a}{d a},\tag{12}$$

Because the semi-elasticity of r with respect to b is positive, the semi-elasticity with respect to α_u is also positive if G first order stochastically dominates F for $w \geq r$. The semi-elasticity of the job leaving rate is positive for wages where the same relation holds between F and G . Because an increase in r decreases the job finding rate for the unemployed, stochastic dominance is not sufficient for a positive semi-elasticity of the job finding. All semi-elasticities are 0 if $F = G$.

The elasticity of the job finding rate while employed is positive for all w if G first order stochastically dominates F . It is zero if the two distributions are equal.

2.2 Endogenous search method

- Until now we have assumed that the channel by which job offers arrive is exogenous. We now consider the case that the search method is chosen by the job seekers. To be specific, we assume that the arrival rates are under control of the

job seeker, and that search costs increase with the arrival rates.² For convenience, we do not consider the decision whether to search or not in detail. We focus on optimal behavior of those who search. In obvious notation we specify that search costs equal

$$c_{kh} = c_{kh}(\lambda_{kh}) \quad (13)$$

with $k = u, e$ and $h = f, g$, and

$$c_{kh} = 0, \quad c'_{kh} > 0, \quad c''_{kh} > 0 \quad (14)$$

For the unemployed the search costs are $c_{uf}(\lambda_{uf}) + c_{ug}(\lambda_{ug})$, and for the employed they are $c_{ef}(\lambda_{ef}) + c_{eg}(\lambda_{eg})$. If the search costs do not depend on the arrival rates, then (6) still holds if we subtract $c_{uf} + c_{ug} - c_{ef} - c_{eg}$ from b .

Introducing search costs in the equations (1) and (2), we obtain the following first order conditions, which hold in case of an interior solution for λ_{kh}

$$c'_{uf}(\lambda_{uf}) = \int_r^\infty [W(x) - R] dF(x) \quad (15)$$

$$c'_{ug}(\lambda_{ug}) = \int_r^\infty [W(x) - R] dG(x) \quad (16)$$

$$c'_{ef}(\lambda_{ef}) = \int_w^\infty [W(x) - W(w)] dF(x) \quad (17)$$

$$c'_{eg}(\lambda_{eg}) = \int_w^\infty [W(x) - W(w)] dG(x) \quad (18)$$

These equations set the marginal cost of a change in the arrival rate equal to its marginal return. Note that in general λ_{kh} depends on all structural parameters of the model.

The first order conditions have a number of testable implications. If $c'_{kh}(0) > 0$, then there is a wage rate w_{kh} such that the optimal arrival rate $\lambda_{kh}^* = 0$ for $w \geq w_{kh}$. If e.g. $c'_{kf}(0) > c_{kf}(0)$, then the employed with a wage $w \geq w_{kf}$ will only use the informal channel to obtain job offers. Differentiating (17) with respect to w we obtain

$$c''_{ef}(\lambda_{ef}) \frac{\partial \lambda_{ef}}{\partial w} = -W'(w) \bar{F}(w) \quad (19)$$

Since $W'(w) > 0$, this implies that the arrival rate decreases with the wage. Moreover, the right-hand side of this equation only depends on model parameters and on w .

²The case in which a single search method is used is a corner solution.

The effect of a change in the marginal search costs can be obtained by specifying equation (2.14) as $c_{kh} = \gamma_{kh} c_{kh}(\lambda_{kh})$ with γ_{kh} a constant. Upon differentiating (17) with respect to γ_{ef} we find

$$\gamma_{ef} c_{ef}''(\lambda_{ef}) \frac{\partial \lambda_{ef}}{\partial \gamma_{ef}} + c_{ef}'(\lambda_{ef}) = 0 \quad (20)$$

so that

$$\frac{\partial \lambda_{ef}}{\partial \gamma_{ef}} < 0 \quad (21)$$

i.e. an increase in the marginal cost of obtaining an offer from a channel results in a lower arrival rate. This implication will be tested in Section 5.

Finally, if the cost functions do not depend on the labor market position, then it is easily seen from equations (15) to (18) that

$$\begin{aligned} \lambda_{uf} &= \lambda_{ef} \\ \lambda_{ug} &= \lambda_{eg} \end{aligned} \quad (22)$$

and hence $r = b$.

Denote

$$\eta_{kh} = \frac{c_{kh}''(\lambda_{kh})}{c_{kh}'(\lambda_{kh})} \frac{\lambda_{kh}}{\partial \ln \lambda_{kh}} = \frac{\partial \ln c_{kh}'(\lambda_{kh})}{\partial \ln \lambda_{kh}} \quad (23)$$

Dividing (19) by (17) we obtain

$$\frac{\eta_{ef}}{\lambda_{ef}} \frac{\partial \lambda_{ef}}{\partial w} = - \frac{W'(w)}{E_F(W(x) - W(w) | x \geq w)} \quad (24)$$

in which E_F indicates integration with respect to $dF(x | x \geq w)$. Hence, we have

$$\frac{\partial \ln \lambda_{ef}}{\partial \ln \lambda_{eg}} = \frac{E_G(W(x) - W(w) | x \geq w) \eta_{eg}}{E_F(W(x) - W(w) | x \geq w) \eta_{ef}} \quad (25)$$

From this we conclude that a sufficient condition for the ratio $\lambda_{ef}/\lambda_{eg}$ to be independent of w is

$$F(x | x \geq w) = G(x | x \geq w) \quad (26)$$

and

$$\eta_{eg} = \eta_{ef} \quad (27)$$

Hence the equality of the truncated offer distributions is not sufficient for the composition of wage offers to be independent of w . This is to be expected, since costs as well as returns affect the optimal search intensities.

Because the optimal arrival rates depend on w , we do not have a closed form solution for $W(w)$ and hence not for r . This poses problems in the structural estimation of the model with endogenous arrival rates. In the empirical analysis we shall test whether the second (informal) method is endogenous by testing observable implications of the model with choice of arrival rates.

3 The data

The data set we use is taken from the OSA (Netherlands Organization of Strategic Labor Market Research) Panel. The OSA collects extensive information on labor market histories of a random sample of households. The survey concentrates on individuals who are between 15 and 61 years of age, and who are not full-time students. Therefore only households with at least one person in this category are included. All individuals (and in all cases the head of the household) in this category are interviewed. Presently four waves are available (April-May 1985, August-October 1986, August-November 1988, and August-November 1990). The first wave consists of 4020 individuals (in 2132 households). In 1990, 1384 (34%) of these individuals are still in the panel. In the waves of 1986, 1988 and 1990 refreshment samples are drawn, so that in 1990 the sample size is 4438 individuals.

The information on the labor market histories of the respondents consists of a sequence of labor market states and the sojourn times in these states. The following labor market states are distinguished: employment (job-to-job transitions are recorded), self-employment, unemployment and not-in-the-labor-force. The latter group consists of homemakers, conscripts, full-time students and persons with other positions that are not related to the labor market. A number of variables that give a more detailed description of the various positions is also recorded, notably income³ (net wages for the employed) and occupation. Part of the information is retrospective. In the first wave of April-May 1985 respondents were asked for their labor market histories from January 1, 1980 until the date of the first interview. We also have information on individual characteristics (age, nationality, gender, education level) at the time of the first interview of the respondent, and an attempt was made to keep track of changes in time-varying

³Income changes at transitions before the date of the first interview are only recorded to lie in one of a few broad intervals. So income in positions occupied before the first interview is reported inaccurately relative to income in later positions, which is not categorized.

characteristics like family composition, marital status and level of education.

The data set provides two types of information on search methods. The first type concerns the search method that is currently used. In each wave individuals are asked if they are searching for a job, and, if so, what search methods they use. Moreover, they are asked to rank the methods in order of importance. There are two problems with the use of this information. First, the translation of categories like ‘most important’, ‘second most important’, etc. to search intensities is not straightforward. Second, for the employed there is an ambiguity in the question that makes it unclear whether the reported search methods were used to obtain the current job or whether they are used to obtain a future job. For that reason, we use a second type of information on search methods. In each wave, the employed individuals are asked by which search method they obtained their current job. The information is retrospective and has all the problems that come with retrospective questions. For instance, if more than one job is found between the interviews, only the search method for the last job is reported, and the search method for the previous jobs is missing.

In our model we distinguish between formal and informal search methods. Some authors consider more categories. For instance, Lindeboom, Van Ours and Renes (1994) distinguish between advertisements, the employment office and informal methods. We classify the first two methods as formal. Informal search methods involve referral by other employees, so they employ the social network of the job seeker. Examples are job offers obtained through the former job, school, a position as trainee, volunteer work, work while retaining unemployment benefit etc. The OSA panel also contains information on the social network of individuals, which may be of importance for the use of the informal search method. In particular, respondents are asked to classify their number of friends and acquaintances as (1) very large, (2) quite a lot, (3) not that much/normal, (4) a few or (5) none. We use this information to create a simple social network indicator which is one if the response to this question equals (1) or (2) and zero otherwise.

In this paper we restrict attention to the respondents who were either working or unemployed at the time of the first interview. Note that this first interview is not always in 1985, as refreshment samples are drawn in 1986, 1988 and 1990. Individuals who were self-employed for some period during the time span covered by the survey are omitted, as well as respondents who are observed to be working in a part-time job or who are observed to be a nonparticipant for some period.

• The reason is that the model of Section 2 only allows for unemployment-job, job-job and job-unemployment transitions. Employed individuals whose wage at the date of the first interview is missing, are omitted. Finally, since almost all

information on accepted wages and search methods comes from individuals who are younger than 39 years of age, we only consider this group. This leaves us with 2068 individuals.

In Table 1 we present descriptive statistics for the full sample and the subsample which is used to estimate the model. The exclusion of respondents who at some moment are observed to be self-employed, nonparticipant, or part-time employee, or are older than 38 years results in a sample that is younger, predominantly male, higher educated, has a higher occupation level, and a somewhat lower net income. Note that the fraction of unemployed individuals among those who are either unemployed or hold a full-time job in the full sample does not differ from the corresponding fraction in the subsample.

Table 2 presents descriptive statistics on the unemployment and job durations. The fraction of left censored spells is the fraction of spells that is in progress at the date of the first interview.

Table 3 contains some descriptive statistics on the relation between search method, accepted wages and job durations in the subsample. From this table, we see that on average wages of jobs found by referral are higher than those found by application. This is true both at the time of the first interview, and for the wages accepted during the observation period, although the latter difference is smaller and not significant. It should be noted that the search method reported in the first interview need not be the method that was used to obtain the job held at that date, and that the cross-section distribution of wages differs from the wage offer distribution. Because high wages are more likely in the cross-section, we expect a larger difference for the cross-sectional distribution than for the distribution of accepted wages. The higher wage of jobs found with informal search need not imply that wage offers are indeed higher for that search method. First, the reservation wages (r for the unemployed and the current wage for the employed) vary in the sample, so that the distribution of accepted wages may differ substantially from the wage offer distribution. Secondly, individuals with characteristics that make them more likely to obtain informal offers may also receive better wage offers. The correlation through the (unobserved) characteristics of the individual is magnified in the cross-section at the time of the first interview because individuals with higher wages are overrepresented in the cross-section. The effect of individual heterogeneity is also apparent from the difference in the fraction of jobs found by the informal search method in the cross-section and among the accepted jobs. In the cross-section the difference is magnified if the jobs found by referral have a shorter duration than those found by application. The last row indicates that this may indeed be the case. The empirical model

Table 1: Comparison of the full sample and the subsample used in the estimation of the model

	full sample		subsample	
	mean	st .dev of mean	mean	st .dev of mean
Age	36.6	0.14	31.2	0.20
Male	0.50	0.0055	0.61	0.011
Education Level'				
- Primary/lower sec.	0.46	0.0056	0.37	0.011
- Intermediate	0.37	0.0054	0.41	0.011
- Higher	0.13	0.0038	0.18	0.0085
- University	0.031	0.0019	0.042	0.0044
Job Level''				
- Un/semi-skilled	0.48	0.0055	0.23	0.0092
- Skilled	0.30	0.0051	0.50	0.011
- Semi-specialized	0.077	0.0029	0.12	0.0072
- Specialized	0.14	0.0039	0.15	0.0079
Working week (hours)	37.7	0.17	38.2	0.26
Labor market position				
- Unemployed	0.070	0.0028	0.12	0.0073
- Full-time job	0.53	0.0057	0.88	0.0073
- Part-time job	0.083	0.0030		
- Self-employed	0.038	0.0021		
- Not-in-labor-force	0.28	0.0050		
Individual net income (guilders/month)	1783	12.5	1728	18.4
Marital Status				
- Married/cohab.	0.76	0.0047	0.68	0.010
- Single	0.24	0.0047	0.32	0.010
Number of observations	8121		2068	

'Education Level: Primary/lower secondary means that the attained level of education is at most lower secondary, either in the general stream (MAVO or at most 3 years of HAVO or VWO) or the vocational stream (LBO). Intermediate means that the attained education level is secondary, again either in the general stream (completed HAVO or VWO) or the vocational stream (MBO). Higher is the level attained after a higher vocational (HBO) or incomplete college training, and University refers to college graduates.

''Occupational level: classification of the Department of Social Affairs. The distinction between semi-specialized and specialized jobs is based on the required level of theoretical knowledge: considerable for semi-specialized and very considerable/scientific for specialized jobs.

Table 2: Unemployment and job durations; durations in months

	unemployment durations	job durations
Fraction left-censored	0.43	0.29
Fraction right-censored	0.49	0.44
Fraction transition to Other Job		0.90
Unemployment		0.10
Average duration	22.6	52.6

Table 3: Accepted jobs found by formal/informal (O/I) method; wages in guilders/month, durations in months

	formal method		informal method	
	mean	st.dev of mean	mean	st .dev of mean
Wage at time of first interview	1801	24.0	1944	27.0
Accepted wages while employed	2063	103.0	2135	96.1
Search method for job at first int.	0.46	0.016	0.54	0.016
Search method for accepted jobs while employed	0.41	0.047	0.59	0.047
Average job spell at time first int.	54.0		52.1	
Extensive social network	0.62	0.011	0.70	0.011

that is specified in Section 4 takes account of these selectivity issues, so that we obtain an unbiased test of the equality of the wage offer distributions.

The last row shows that job seekers who during the observation period find a job by referral have indeed a more extensive social network than job seekers who find a job by a formal search method. This is used in Section 5 in a test for the endogeneity of search methods.

Evidence on the use of search methods in consecutive jobs is given in Table 4. For individuals with two job spells during the observation period we give the fraction that uses the same search method on both occasions. Note that the persistence is somewhat larger for individuals who use the informal method. However, a substantial fraction of job seekers obtains a job with a different search method. This is in line with our economic model.

Table 4: Fraction of subsequent jobs found by formal/informal (O/I) method

search method job at first interview	search method of subsequent job
formal	0.45 (0.088)
informal	0.76 (0.060)
all	0.62 (0.058)

4 Empirical implementation

4.1 Identification

The unknown entities of the economic model of Section 2 are λ_{uf} , λ_{ug} , λ_{ef} , λ_{eg} , δ , ρ , and the wage offer distributions F and G . In this subsection we consider whether these are identified from the data at hand. For the moment we assume that the population consists of identical individuals in a homogeneous labor market, and we ignore measurement errors. In addition, for the moment, we treat r as a parameter (later on we verify that the behavioral equation for r does not contain additional identifying information), so that ρ disappears from the model. The data basically consist of wages, durations and transitions. The wage data are accepted wages by the employed or unemployed, where we know which search method generated the accepted job. We also have data on wages in a cross-section of workers (at the time of the first interview). The accepted wages of the

unemployed are drawings from $F(w|w \geq r)$ in case of a wage offer found with the formal search method and $G(w|w \geq r)$ in case of a wage offer found with the informal method. If w_0 denotes the previous wage, then the accepted wages of the employed are drawings from $F(w|w \geq w_0)$ and $G(w|w \geq w_0)$, respectively. Note that w_0 necessarily exceeds r , since w_0 has been accepted at an earlier instant. Now consider wages in a cross-section of workers. These wages also exceed r . However, without imposing steady state conditions as in equilibrium models (see e.g. Ridder and Van den Berg (1997)), we cannot relate the distribution of these wages to the wage offer distribution. Somewhat arbitrarily, we denote the distribution of cross-sectional wages by $K(w|w \geq r)$.

The duration data consist of unemployment durations and job durations. The model of Section 2 implies that these durations follow exponential distributions (of course, in case of job durations, we have to condition on the current wage). More precisely, taking into account the search method by which the (next) job is found, we have competing risks with constant exit-specific hazards. For the unemployment durations these hazards are given in equations (7): $\theta_{uf} = \lambda_{uf}\bar{F}(r)$ and $\theta_{ug} = \lambda_{ug}\bar{G}(r)$. For the job durations these hazards are given by equations (8), which can be rewritten as

$$\begin{aligned}\theta_{ef}(w_0) &= \lambda_{ef}\bar{F}(r)\bar{F}(w_0|w_0 \geq r) \\ \theta_{eg}(w_0) &= \lambda_{eg}\bar{G}(r)\bar{G}(w_0|w_0 \geq r) \\ \theta_{eu} &= \delta\end{aligned}\tag{28}$$

We are now in a position to discuss the identification of the model. It is well known that, without additional assumptions or additional information, the wage offer distribution and the job offer arrival rate are not identified in the empirical analysis of job search models (Flinn and Heckman (1982)). Basically, it is not possible to distinguish between (i) a large job offer arrival rate and a small acceptance probability (of the unemployed), and (ii) a small job offer arrival rate and a large acceptance probability. Only the product of the arrival rate and the acceptance probability is identified. In our model this problem is manifest for both search methods, as is clear from the expressions above. We can only identify $\lambda_{uf}\bar{F}(r)$, $\lambda_{ug}\bar{G}(r)$, $\lambda_{ef}\bar{F}(r)$, $\lambda_{eg}\bar{G}(r)$, δ , r (which is basically identified from the smallest wage in the data), and the truncated distributions $F(w|w \geq r)$ and $G(w|w \geq r)$.

The difference $E_F(w|w > r) - E_G(w|w > r)$ of the conditional means summarizes the differences between the distributions of acceptable wages, and as such it is a parameter of interest. However, if the conditional mean associated with F

exceeds that of G but the acceptance probability for F falls short of that for G , then obviously this has different implications than if the orderings of conditional means and acceptance probabilities are the same. For example, in the former case, a policy subsidizing the use of formal search methods would not be as fruitful as it would be in the latter case.

In the appendix to this paper we digress on the relation between the conditional mean and the acceptance probability, in a general class of probability distributions. This is used to relate the sign of $\bar{F}(r) - \bar{G}(r)$ to the sign of $E_F(w|w > r) - E_G(w|w > r)$, if F and G belong to this general class of functions. It turns out that, in this general class, the acceptance probability and the conditional mean of two distributions always satisfy the same ordering. This result is useful when interpreting the estimation results. Assume that both F and G belong to this general class of functions. If it is observed that the conditional mean of F exceeds that of G , then the acceptance probability for F also exceeds that for G , so job offers from F will be turned down less frequently. This means that any observed difference in the conditional mean wages provides a conservative estimate of the relative attractiveness of the formal search method. The opposite holds if the conditional mean of G exceeds that of F . The parametric families of distributions for F and G that we adopt in the empirical analysis are such that F and G always belong to this general class of functions (see Subsection 4.2 and the appendix).

It is important to stress that the analysis in the appendix is not related to the so-called *recoverability* issue, which is of importance in the identification of search models (Flinn and Heckman (1982)). Suppose that we assume that both F and G belong to specific families of distributions that are not closed under truncation⁴. Then both F and G are fully identified (“recoverable”) from their truncated versions $F(w|w \geq r)$ and $G(w|w \geq r)$. As a result, in that case, the acceptance probabilities $\bar{F}(r)$ and $\bar{G}(r)$ and the job offer arrival rates λ_{uf} , λ_{ug} , λ_{ef} and λ_{eg} are identified as well. The parametric families of distributions for F and G that we adopt in the empirical analysis below are not closed under truncation, so both distributions are recoverable. Hence, the full model is identified. It is however clear that the estimation results will be extremely sensitive to arbitrary functional form restrictions concerning F and G . We therefore choose not to exploit this in the empirical analysis.

So far we have assumed that all individuals are identical. In Section 5 we

⁴A parametric family of distributions $F(w; \theta)$, $\theta \in \Theta$ is closed under truncation if for all $r_1 \neq r_2$ there are parameter vectors θ_1 and θ_2 such that $F(w|w \geq r_1; \theta_1) \equiv F(w|w \geq r_2; \theta_2) \vee w \geq \max(r_1, r_2)$

exploit heterogeneity across individuals in order to test the null hypothesis that $\bar{F}(r)$ and $\bar{G}(r)$ are equal. We also exploit this heterogeneity to test whether these acceptance probabilities are equal to one. The latter seems to be an empirical regularity (see for example Devine and Kiefer (1991) for a survey). In that case, truncated and untruncated wage offer distributions are identical.

Finally the reservation wage equation in (6) can be rewritten in terms of identified quantities.

$$r = b + \int_r^\infty \frac{(\theta_{uf} - \theta_{ef}) \bar{F}(w|w \geq r) + (\theta_{ug} - \theta_{eg}) \bar{G}(w|w \geq r)}{\rho + \delta + \theta_{ef} \bar{F}(w|w \geq r) + \theta_{eg} \bar{G}(w|w \geq r)} dw \quad (29)$$

Hence ρ can be identified, irrespective of whether F and G are recoverable.

4 . 2 Parameterization

This subsection deals with two types of parameterization. First, we specify parametric functional forms for the wage (offer) distributions which are faced by the individual searcher. Secondly, to capture the way in which the economic (structural) parameters vary across different individuals, we write them as regression-like functions of individual characteristics. In both cases, we only parameterize and estimate economic parameters that are identified. We do not pretend to estimate the job offer arrival rates or the probability masses below the reservation wage r . As noted in the introduction, such an approach to the parameterization of the job search model is novel.

Throughout most of the empirical analysis we assume that the individual $F(w|w > r)$, $G(w|w > r)$ and $K(w|w > r)$ are transposed lognormal distributions. In particular, we assume that the random variables associated with $F(w|w > r)$, $G(w|w > r)$ and $K(w|w > r)$ can be written as the sum of r and a random variable that is lognormally distributed. Thus, the corresponding densities are obtained by shifting lognormal densities to the right such that the lower bound of the support moves from 0 to r . Note that these are specifications for the truncated wage (offer) distributions, so we do not rule out that the untruncated distributions have probability mass below r .

The parameters of the economic model may vary across individuals. Let a vector x of observed individual characteristics summarize the individual heterogeneity in the data. We distinguish between three age categories (16-22, 23-29, 30-38), three levels of education (primary/lower secondary, intermediate,

higher/university) and three job levels (un/semi-skilled, skilled, (semi-)specialized)⁵. For our purposes, it is appealing to interpret these characteristics as defining separate segments of the labor market. Note that equilibrium search models predict that if workers within a segment are homogeneous, then firms set wages such that the unemployed always accept all wage offers, so that the acceptance probabilities for the unemployed are equal to one (see Ridder and Van den Berg (1997) and Bontemps, Robin and Van den Berg (1997)).

The data set is not sufficiently large to estimate the model separately for different subsets of homogeneous individuals. We therefore estimate a parameterized model in which the economic parameters are written as regression-like functions of individual characteristics. For computational and expositional convenience, these parameterizations are specified as linear or log-linear functions of x , so we do not allow for interaction effects.

The parameters of the transposed lognormal wage (offer) distributions are μ_h and σ_h^2 , $h = F, G, K$, where we specify that

$$\mu_h = \gamma_h + \gamma'x \quad (30)$$

while σ_h is assumed to be independent of x .

The identified transition rates are specified as log-linear in the individual characteristics. For the rates into and out of unemployment this gives

$$\begin{aligned} \theta_{uf} &= \exp(\beta_{0f} + \beta'_f x) \\ \theta_{ug} &= \exp(\beta_{0g} + \beta'_g x) \\ \theta_{eu} &= \exp(\beta_{0\delta} + \beta'_\delta x) \end{aligned} \quad (31)$$

These parameterizations are supposed to capture the way in which the corresponding economic entities ($\lambda_{uf}\bar{F}(r)$, $\lambda_{ug}\bar{G}(r)$ and δ) vary across individuals.

From equations (7) and (28) it follows that the channel-specific exit rates out of a job with a wage w can be expressed as

$$\begin{aligned} \theta_{ef}(w) &= (\lambda_{ef}/\lambda_{uf})\theta_{uf}\bar{F}(w|w \geq r) \\ \theta_{eg}(w) &= (\lambda_{eg}/\lambda_{ug})\theta_{ug}\bar{G}(w|w \geq r) \end{aligned}$$

Now define θ_{ef} and θ_{eg} simply as the exit rates out of a job with a wage equal to r , so e.g. $\theta_{ef} := \theta_{ef}(r) = (\lambda_{ef}/\lambda_{uf})\theta_{uf}$. We specify $(\lambda_{ef}/\lambda_{uf})$ as $\exp(\beta_{ef})$, and $(\lambda_{eg}/\lambda_{ug})$ as $\exp(\beta_{eg})$. As a result,

⁵See Table 1 for an explanation of these categories.

$$\begin{aligned}\theta_{ef} &= \exp(\beta_{0f} + \beta'_f x + \beta_{ef}) \\ \theta_{eg} &= \exp(\beta_{0g} + \beta'_g x + \beta_{eg})\end{aligned}\tag{32}$$

Alternatively, one could specify $(\lambda_{ef}/\lambda_{uf})$ and $(\lambda_{eg}/\lambda_{ug})$ as log-linear regression-like functions of x . Then the coefficients associated with x in equations (32) would be different from β_f and β_g . For practical reasons we do not pursue such a parameterization.

Equations (32) complete the parameterization of the transition rates given r . For example, the transition rate $\theta_{ef}(w)$ is now specified as $\theta_{ef}\bar{F}(w|w \geq r)$, with θ_{ef} and F as specified above.

At this stage it is useful to mention that we use a two-stage procedure to estimate the model. In the first stage we estimate the transition rates and the parameters of the wage (offer) distributions. Moreover, in the first stage, we adopt a parameterization of the reservation wage r , which is supposed to capture the variation in r across heterogeneous individuals, and we estimate the corresponding coefficients along with the other parameters,

$$r = \exp(\eta_0 + \eta'_r x)\tag{33}$$

This equation is not to be confused with the Bellman equation (6) for the optimal individual reservation wage. The equation above captures variation of reservation wages across unemployed workers with different characteristics, and it does not impose the values that are optimal according to the theoretical model.

As a result, in the first estimation stage, the empirical specification for the exit rate out of unemployment is equivalent to a reduced-form specification. Note however that the empirical specifications above for the transition rates from one job to another are structural in the sense that they impose optimal behavior of employed workers. We exploit the equation for the optimal reservation wage in the second estimation stage, and we exploit variation in structural determinants of r across individuals for further inference in Subsection 5.2. In particular, in the second estimation stage, we estimate ρ from the empirical version (29) of the Bellman equation for the reservation wage. The solution of this equation for ρ will be different for individuals with different x , and we adopt nonlinear least squares to obtain the value which gives the best over-all fit.

We allow for measurement error in the (accepted) wages. There is ample evidence that the wages in the OSA panel are measured with error (see e.g. Hartog and Van Ophem (1991)). Moreover, if we do not allow for measurement

error, the reservation wage r is estimated as the sample minimum of the observed (accepted) wages and this estimator can be severely biased if wages are measured with error. We assume that the measurement error is multiplicative so that the observed (accepted) wages are given by

$$\tilde{w} = w\varepsilon \quad (34)$$

with

$$\varepsilon \sim \text{LN}(\mu_\varepsilon, \sigma_\varepsilon^2) \quad (35)$$

in which we normalize μ_ε such that $E(\varepsilon)=1$. The measurement errors of the wages of consecutive jobs are assumed to be independent.

Now let us briefly discuss the construction of individual likelihood contributions in the first estimation stage. The economic model implies that unemployment durations and job durations are exponentially distributed. This simplifies the derivation of the likelihood function of the observed labor market histories considerably (Ridder (1984)). We use the following information: the labor market position (job or unemployed) at the date of the first interview, the elapsed duration in that position, and the remaining duration in that position. If the position is left before the end of the observation period, then we observe the type of transition (job-to-job by formal or informal method, job-to-unemployment, unemployment-to-job by formal or informal method) and the time spent in the new position. We follow the individuals to the end of the observation period or until the end of the second spell, and in the latter case we observe the type of transition at the end of the second spell. The number of transitions is limited to two for computational reasons: the dimension of the numerical integration of the measurement errors is equal to the number of consecutive job spells.

The elapsed and residual unemployment durations at the time of the first interview are stochastically independent and exponentially distributed with parameter $\theta_{uf} + \theta_{ug}$. A subsequent transition to a job found by a formal method has probability $\theta_{uf}/(\theta_{uf} + \theta_{ug})$. The elapsed and residual job duration at the time of the first interview are independently exponentially distributed with parameter $\theta_{ef}(w_0) + \theta_{eg}(w_0) + \delta$, with w_0 the wage at the first interview, which is itself distributed according to $K(w|w > r)$. A subsequent transition to a higher paying job found by a formal method has probability

$$\frac{\theta_{ef}(w_0)}{\theta_{ef}(w_0) + \theta_{eg}(w_0) + \delta} \quad (36)$$

with similar probabilities for the other two possible transitions. The wage in the next job has density

$$f(w_1|w_1 \geq w_0) \quad (37)$$

if found by a formal search method and density

$$g(w_1|w_1 \geq w_0) \quad (38)$$

if found by an informal search method. The new job spell is exponentially distributed with parameter $\theta_{ef}(w_1) + \theta_{eg}(w_1) + 6$. A subsequent unemployment spell follows an exponential distribution with parameter $\theta_{uf} + \theta_{ug}$. The full individual likelihood contribution is subsequently obtained by integration with respect to the joint distribution of measurement errors of the observed wages (see Van den Berg and Ridder (1997) for details).⁶

Now let us turn to the second estimation step. The objective function to be minimized here is defined as

$$\sum_i^n (\hat{r}_i - \tilde{r}_i - z)^2 \quad n = 27 \quad (39)$$

Here, the subscript i refers to the type of individual. Since we use three individual characteristics with three possible values each, we distinguish between 27 different types of individuals. The variable \hat{r}_i is the estimated type-specific reservation wage from the first estimation step, while \tilde{r}_i is the reservation wage that follows from the behavioral reservation wage equation (29). The only unknown parameter in the latter equation is p . We introduce an additional unknown parameter z in the objective function (see above). If the behavioral equation for r is correctly specified then z is zero. Allowing for $z \neq 0$ therefore provides a natural specification test of the model. The benefits level b_i is taken to be the mean of unemployment benefits for all individuals with similar x who are unemployed at the first interview.

5 Estimation results

5.1 Parameter estimates

Tables 5 to 7 present the parameter estimates for the empirical model. The unit time period is one month. Table 8 presents implied values of the transition rates,

⁶The likelihood function was maximized with the BFGS algorithm. The integrals were obtained by the Gauss-Legendre algorithm. All computations were performed in GAUSS.

the conditional mean of the wage (offer) distributions and the reservation wage. We start by discussing the parameter estimates for the transition rates, which are presented in Table 5.

Table 5: Parameter estimates: transition rates (standard errors)

variable/parameter	formal		informal	
<i>Job finding rate by search method</i>				
constant	-3.73	(0.28)	-2.89	(0.19)
age category 23-29	-0.49	(0.13)	-0.74	(0.094)
age category 30-38	-1.11	(0.13)	-1.40	(0.098)
intermediate education	0.20	(0.10)	0.059	(0.080)
higher education/university	0.82	(0.13)	0.18	(0.12)
job level: skilled	0.32	(0.12)	-0.20	(0.084)
job level: (semi)-specialized	0.19	(0.14)	-0.11	(0.11)
extensive social network	-0.021	(0.10)	-0.035	(0.084)
employed	0.32	(0.25)	0.44	(0.22)
<i>Layoff rate</i>				
constant	-4.64	(0.28)		
age category 23-29	-0.41	(0.27)		
age category 30-38	-0.63	(0.26)		
intermediate education	-0.64	(0.22)		
higher education/university	-0.50	(0.30)		
occupation level: skilled	-0.076	(0.22)		
occupation level: (semi-)specialized	-0.012	(0.30)		

The parameters indicate how the product of the acceptance probability and the arrival rate varies over the population. Although a structural interpretation is impossible, some interesting patterns emerge. First, as usual, the transition rates decrease with age. For the formal search method, the transition intensity increases with the level of education. This is not true for the informal search method. The arrival rate is somewhat larger for the employed, but only significantly for the informal search method.

Table 6: Parameter estimates: wage (offer) distributions and the reservation wage; wages in 1000 guilders/month (standard errors)

variable/parameter	coefficient	standard error
<i>Wage (offer) distributions</i>		
μ_F	6.00	(0.30)
μ_G	6.16	(0.27)
μ_K	6.15	(0.26)
age category 23-29	0.11	(0.11)
age category 30-38	0.56	(0.093)
intermediate education	0.089	(0.066)
higher education/university	0.27	(0.076)
occupation level: skilled	0.038	(0.079)
occupation level: (semi-)specialized	0.47	(0.10)
σ_F	0.42	(0.10)
σ_G	0.41	(0.094)
σ_K	0.26	(0.046)
σ_ε	0.18	(0.0048)
<i>Reservation wage</i>		
constant	6.59	(0.17)
age category 23-29	0.42	(0.072)
age category 30-38	0.29	(0.083)
intermediate education	0.025	(0.050)
higher education/university	0.02s	(0.071)
occupation level: skilled	0.040	(0.059)
occupation level: (semi-)specialized	-0.17	(0.12)
-Log Likelihood = 34131.2		

Table 6 presents the parameter estimates for the wage (offer) distributions and the reservation wage equation. Most of the parameter estimates of the wage (offer) distributions are in accordance with intuition. Wages increase with age, educational level and occupational level. The key estimation result is that the hypothesis that the truncated wage offer distributions are equal cannot be rejected. The null hypotheses $\mu_F = \mu_G$ and $\sigma_F = \sigma_G$ cannot be rejected in a Wald test. This is confirmed if we perform a Likelihood Ratio test on the two restrictions. The test statistic equals 4.05 ($\chi^2_{0.90}(2) = 4.61$).

Generally, the estimated reservation wages are close to and even below the benefit level. Since the benefits level is often smaller than the mandatory minimum wage, this is a first indication that there are few, if any, wage offers below the reservation wage.

We investigated the robustness of the results by including additional independent variables, like marital status, gender, and the number of individuals working in the household. The estimates of the parameters of the wage offer distributions are not sensitive to the inclusion of these variables.

Furthermore, the results are robust to changes in the lower bound of the support of the wage offer distributions. We re-estimated the model where the lower bound of the support of the wage (offer) distributions is set equal to the reservation wage minus a fixed amount. As a result, the acceptance probabilities are positive, and the density of the untruncated wage (offer) distributions is not a priori restricted to equal zero at the reservation wage. For various fixed lower bounds ($r - 100, r - 250, r - 400$), the hypothesis that both wage offer distributions are equal is not rejected. Further, the fit of the model deteriorates if the lower bound is decreased (the log-likelihood values are -34131.2, -34141.7 and -34143.4, respectively). The parameters of the transition rates are unaffected by these changes.

Table 7 reports the parameter estimate of the discount rate that is obtained in the second stage of the estimation. The estimate implies a discount rate of 13% per year. This result is similar to estimates in other structural analyses of job search (e.g. Van den Berg (1990a) estimates a discount rate of 12%). The estimated constant z is significant. We conclude that the reservation wage condition as stated in equation (6) is not valid. We can interpret this result in two ways. First, it may be that the nonpecuniary utility of unemployment is positive, and that this utility term can be expressed by an additive and constant utility flow with monetary value z . In that case the utility flow from being unemployed equals $b + z$. A second explanation derives from the fact that the reservation wage may be smaller than the lower bound of the support of the wage (offer)

Table 7: Parameter estimates: the subjective discount rate

parameter	coefficient	standard error
ρ (subjective rate of discount)	0.011	(0.0086)
z (constant term)	179.4	(69.8)
Standard error sum of squares	189.9	(185.5)

distributions. In that case the estimated lower bound in the first stage is larger than r , and the estimate of z will be positive.

5.2 How frequently do the unemployed reject job offers, and are search intensities endogenous?

As argued in Section 4, if the truncated wage offer distributions are equal then the untruncated wage offer distributions are not necessarily equal. In particular, we cannot infer whether the acceptance probabilities $\bar{F}(r)$ and $\bar{G}(r)$ are equal. Now, from the robustness checks in the previous subsection it appears that the reservation wage does not exceed the lower bound of the support of the wage offer distributions (recall that the fit of the model does not improve if we allow the reservation wage to exceed the lower bound of the support of the wage offer distributions). So, under the untestable functional form assumptions we made there, we may conclude that both acceptance probabilities are equal to one. However, instead of relying on the recoverability of the accepted wage offer distributions, or on the fact that the estimated reservation wages are generally below the mandatory minimum wage, we propose an alternative test of the hypothesis that the acceptance probabilities are equal (and, in particular, that they are equal to one). This test exploits heterogeneity across individuals.⁷

Consider individuals who differ in terms of their unemployment benefits level b . The exit rate out of unemployment depends on b only by way of the reservation

⁷An untruncated distribution can be identified from truncated versions of it if there is sufficient independent variation in the truncation point (which in our case is the reservation wage); see Woodroffe (1985).

Table 8: Implications of parameter estimates, unit time period is one month

<i>Age category</i>				
age category	16-22	23-29	30-38	average
$\theta_{uf}(r)$	0.034	0.026	0.014	0.022
$\theta_{ug}(r)$	0.049	0.025	0.013	0.024
$\theta_{ef}(r)$	0.047	0.035	0.019	0.030
$\theta_{eg}(r)$	0.076	0.038	0.020	0.037
δ	0.0071	0.0043	0.0035	0.0045
$E_F(w w \geq r)$	1247	1755	2021	1778
$E_G(w w \geq r)$	1333	1867	2202	1915
r	744	1096	956	971
b	841	1136	1314	1160
<i>Level of education</i>				
level of education	1	2	3	
$\theta_{uf}(r)$	0.017	0.021	0.033	
$\theta_{ug}(r)$	0.025	0.024	0.022	
$\theta_{ef}(r)$	0.024	0.028	0.045	
$\theta_{eg}(r)$	0.039	0.037	0.034	
δ	0.0065	0.0033	0.0035	
$E_F(w w \geq r)$	1595	1756	2123	
$E_G(w w \geq r)$	1702	1886	2322	
r	963	987	952	
b	1158	1165	1152	

wage. The unemployment benefits affect the reservation wage of unemployed workers, which in turn affects the probability that a job offer is accepted. From the model we derive the following elasticities of the exit rate out of unemployment with respect. to the benefits level:

$$\frac{\partial \ln \theta_{uf}}{\partial \ln b} = \frac{f(r)}{\bar{F}(r)} r \frac{\partial \ln r}{\partial \ln b} \quad \text{and} \quad \frac{\partial \ln \theta_{ug}}{\partial \ln b} = - \frac{g(r)}{\bar{G}(r)} r \frac{\partial \ln r}{\partial \ln b} \quad (40)$$

Under the null hypothesis that $F(w) = G(w)$ on $w \in (0, r]$, both elasticities are equal. Indeed, sufficient for the equality of the elasticities is that the acceptance probabilities $\bar{F}(r)$ and $\bar{G}(r)$ are equal and that the densities f and g have the same value at r . In conclusion, by comparing the way in which exit rates out of unemployment for the two search channels differ across individuals with different b , we can test whether $\bar{F}(r) = \bar{G}(r)$.

Now consider the null hypothesis that the acceptance probabilities are equal to one for all unemployed workers (that is, for all possible values of b in the population). More precisely, we hypothesize that the reservation wage is strictly smaller than the smallest wage offer in the market for all unemployed workers. Then obviously $f(r) = g(r) = 0$, and the elasticities above are zero. Thus, by observing whether the exit rates out of unemployment do not vary with b , we can test whether acceptance probabilities are equal to one.

A number of comments are in order. First of all, in reality we do not observe infinitesimal changes of b , so we have to assume that the elasticities behave as required on a certain interval for r . Secondly, we do not re-estimate the model including the behavioral equation for r in order to obtain an estimate of the effect of b on the exit rates. The result of such a procedure would be heavily dependent on the ad-hoc functional-form specifications of F and G (see e.g. Van den Berg (1990b)). Instead, we include $\log b$ as a regressor in θ_{uf} and θ_{ug} (see equations (31)) and we re-estimate these rates with the unemployment duration data. Thirdly, these tests do not have a large power against certain alternative hypotheses. For example, the supports of F and G may have gaps, e.g. for institutional reasons. If r is located in a common gap, then both elasticities are zero even if neither of the null hypotheses is true. On the other hand, if search intensities are endogenously chosen then, according to Subsection 2.2, b affects the optimal values of the search intensities, and therefore it affects the transition rates.

Now let us turn to the results of these tests. The estimated elasticities equal 0.01 (0.49) and 0.45 (0.48), for the formal and the informal job finding rate, respectively. Both the Wald test and the Likelihood Ratio test indicate that the hypothesis that the elasticities are equal can not be rejected. The hypothesis that

both elasticities are zero can not be rejected either ($\chi^2_2 = 1.85 < 4.60 = \chi^2_{2;0.90}$).⁸ These results fully support the hypothesis that both acceptance probabilities are equal to one, so that the truncated and untruncated distributions coincide. Note that a reservation wage which is lower than the lower bound of the support of w explains the significance of z in the second step in the estimation of the model; apparently, the true reservation wage is not identified from the wage data.

To test for endogeneity of the use of search methods, we use the social network dummy variable. The extent of the social network of individuals is likely to affect the costs of using the informal channel, but not the returns, apart from any difference between F and G . If the arrival rate of informal job offers is affected by the optimally chosen search intensity, then such an indicator of search costs should affect the job offer arrival rates, and hence the transition rates to (other) jobs. We include the social network indicator as an additional regressor in these transition rates. It turns out that the corresponding coefficient is insignificant in each transition rate. This lends credence to the model in which the arrival rates of formal and informal job offers are exogenous (more precisely, workers with identical labor market characteristics choose a common maximum search effort that is exogenously determined).

To summarize, in this subsection we have designed and applied some tests that exploit heterogeneity across individuals. The results indicate that search effort is exogenous. Moreover, job offer acceptance probabilities of the unemployed seem to be equal to one, and truncated and untruncated wage offer distributions coincide. Since there is no evidence that the use of search channels is endogenous, and from the finding that both wage offer distributions do not differ systematically, we conclude that the type of search method used is an irrelevant feature attached to a wage offer. For current labor market participants, a job found by means of one particular channel is not different in any relevant way from a job found by means of the other channel. This does not preclude that a social planner may gain efficiency by subsidizing one channel over the other. Any insights into the latter would require the quantification of various additional aspects of the process by which workers and firms are matched, which is beyond the scope of this paper.

6 Conclusion

This paper provides a structural empirical analysis of job search along formal and informal search channels. We have estimated a job search model in which offers

⁸This result is fully in accordance to the extensive empirical literature of the effect of b on unemployment durations in The Netherlands; see Van den Berg (1990b) for a survey.

arrive by way of these two channels, and in which the wage offer distribution is allowed to depend on the search method that was used to generate the offer. The model allows for search during unemployment as well as search on the job.

The estimation results show that the exit rate to (new) jobs along the informal channel exceeds the exit rate along the formal channel, in unemployment as well as in employment. Highly educated individuals find jobs relatively often along the formal channel. Furthermore, employed individuals receive more job offers than the unemployed. This holds both for formal and informal job offers. The key result is that we do not find a wage advantage of searching formally or informally. This result is robust with respect to a number of possible misspecifications of the model.

The fundamental problem in the identification of the model concerns the fact that the wage offer distributions cannot be recovered from the distributions of accepted wages that are truncated at the reservation wage of the unemployed, if no functional form assumptions are made on the untruncated distributions, and if the population consists of identical individuals in a homogeneous labor market. We choose not to rely on the recoverability of arbitrarily chosen functional forms for these distributions in order to identify the model. Instead, we deal with this in a variety of other ways, theoretical as well as empirical. For both wage offer distributions, we cannot reject the null hypothesis that the probability masses of the wage offer distributions below the reservation wage equal zero. We conclude that the truncated accepted wage distributions equal the untruncated wage offer distributions. The estimation results also indicate that search effort is exogenous.

In sum, since there is no evidence that the use of search channels is endogenous, and from the finding that both wage offer distributions do not differ systematically, we conclude that the type of search method used to find a job offer is an irrelevant feature attached to the wage corresponding to that offer. This conclusion runs against predictions in theoretical studies stating that the informal search method generates job offers with higher wages. Of course, we can not rule out that the informal method has systematic advantages in terms of non-wage characteristics of job offers. It would be an interesting topic for further empirical research to investigate this.

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Appendix: The conditional mean and the acceptance probability

As argued in Section 4, the data identify the truncated (or conditional) distributions $F(w|w > r)$ and $G(w|w > r)$ but not the untruncated distributions $F(w)$ and $G(w)$. In particular, they do identify the conditional means $E_F(w|w > r)$ and $E_G(w|w > r)$, but not the acceptance probabilities $\bar{F}(r)$ and $\bar{G}(r)$. The difference of the conditional means summarizes the differences between the distributions of acceptable wages, and as such it is a parameter of interest. However, if the conditional mean associated with F exceeds that of G but the acceptance probability of F falls short of that of G , then obviously any policy subsidizing the use of formal search channels would not be as fruitful as it would be if the orderings of conditional means and acceptance probabilities are the same.

In this appendix we digress on the relation between the conditional mean and the acceptance probability in general classes of probability distributions. We restrict attention to distributions of “regular” random variables (i.e., nonnegative, continuous, with a finite mean etc.). We want to relate the sign of $\bar{F}(r) - \bar{G}(r)$ to the sign of $E_F(w|w > r) - E_G(w|w > r)$. Note that the first term is nonnegative for all $r > 0$ iff F first-order stochastically dominates G . It should however be noted that first-order stochastic dominance of F over G does not imply first-order stochastic dominance of $F(w|w > r)$ over $G(w|w > r)$. Now let $\psi_F(w)$ and $\psi_G(w)$ denote the **hazard rates** associated with F and G , respectively, so for example $\psi_F(w) = f(w)/\bar{F}(w)$.

Result. *If $\psi_F(w) \leq \psi_G(w)$ for every $w > 0$ then both $\bar{F}(r) \geq \bar{G}(r)$ and $E_F(w|w > r) \geq E_G(w|w > r)$, for every $r > 0$.*

The first part of this result is trivial, since

$$\frac{\bar{F}(w)}{\bar{G}(w)} = \exp \left(- \int_0^w \psi_F(x) - \psi_G(x) dx \right) \quad (41)$$

(see e.g. Lancaster (1990)). The second part follows from the following equality,

$$E_F(w|w > r) - E_G(w|w > r) = \int_r^\infty \exp \left(- \int_r^w \psi_F(x) dx \right) \left[1 - \exp \left(\int_r^w \psi_F(x) - \psi_G(x) dx \right) \right] dw \quad (42)$$

which can be obtained by partial integration (see Van den Berg (1994)).

From the equations above it is clear that both the acceptance probability inequality and the conditional mean inequality can be translated in terms of the functions $\psi_F(w)$ and $\psi_G(w)$. However, the former inequality concerns the shape of these functions on $w \in (0, r)$ while the latter concerns the shape on $w \in (r, \infty)$. Thus, one needs an assumption on the global behavior of ψ_F and ψ_G in order to relate the two inequalities for any r . (It is obvious that the condition in the result above is by no means necessary.)

The usefulness of the result above is in the following: if one is prepared to assume that the hazard rate of F is uniformly larger or smaller than that of G , then the acceptance probabilities and conditional means of F and G satisfy the same ordering. If it is then observed that the conditional mean of F exceeds that of G , then the acceptance probability for F also exceeds that for G , so job offers from F will be turned down less frequently. This means that any observed difference in the conditional mean wages provides a conservative estimate of the relative attractiveness of the search method with the highest conditional mean wage.

Examples of parametric families of distributions for which the parameters define an unambiguous ranking of the hazard rates are the families of exponential distributions and Pareto distributions (provided the latter all have the same support). So, if both F and G are Pareto distributed with the same support, and if the observed conditional mean of F exceeds that of G , then the acceptance probability of F also exceeds that of G .

In the empirical analysis of this paper we mostly adopt lognormal specifications for F and G , with parameters (μ_F, σ_F) and (μ_G, σ_G) , respectively. The hazard rates of F and G are equal to

$$\frac{1}{w} \psi_{SN} \left(\frac{\log w - \mu_i}{\sigma_i} \right) \quad i = F, G \quad (43)$$

in which ψ_{SN} denotes the hazard rate of the standard normal distribution. The function $\psi_{SN}(x)$ is increasing, for all x . Thus, the expression above decreases in both μ_i and σ_i . Let $\sigma_F = \sigma_G$. It follows that if $\mu_F > (<) \mu_G$ then both $\bar{F}(r) > (<) \bar{G}(r)$ and $E_F(w|w > r) > (<) E_G(w|w > r)$, for any $r > 0$. In sum, if F and G are lognormally distributed with the same σ parameter then the acceptance probabilities and conditional means of F and G satisfy the same ordering. The same is true if μ rather than σ is assumed to be the same. Note incidentally that lognormal distributions are recoverable, so μ_F and σ_F (and therefore the acceptance probability $\bar{F}(r)$) are identified from the truncated distribution $F(w|w > r)$ with a fixed r (similarly for G).

Finally, suppose that F and G have transposed lognormal distributions. This parameterization is also used in the empirical analysis of this paper. The random variables associated with F and G can then be written as the sum of a common positive constant a and a random variable that is lognormally distributed with parameters (μ_F, a) and (μ_G, a) , respectively (so their support equals (a, ∞)). The hazard rates of these distributions equal the hazard rates of the corresponding lognormal distributions evaluated at $w-a$ instead of w . As a result, the transposed lognormal case has the same properties as the lognormal case.

All in all, it seems justified to conclude that in many cases the acceptance probability and the conditional mean are either both largest for F or both largest for G . This result is useful when interpreting the estimation results.